Effect of Mission Requirements on the Economic Robustness of an HSCT Concept†

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Abstract

Design for robustness and its subset design for economic robustness and viability are two areas in current design methodology and optimization research attracting a lot of attention, as the increasing number of publications and industry position papers in this field indicate. In fact, these publications attempt to address the paradigm shift taking place in industry, where design for performance is being replaced by design for affordability. That is designing and optimizing a system for a high yield while reducing the variation from that optimum yield. The study presented here can be viewed as a proof of concept for a proposed approach to design for robustness, called Robust Design Simulation (RDS). The paper outlines an alternative approach to Taguchi's, assigning probability distributions to uncontrollable factors (noise variables) which result in a distribution for the design objective instead of a point solution. The study also illustrates that indeed one is able to manipulate the mean and variance of the design objective concurrently, hence, optimizing a new Overall Evaluation Criterion (OEC) that is comprised of both the mean and variance of the design objective. The High Speed Civil Transport (HSCT) was utilized as an illustrative case to demonstrate the implementation of RDS. The objective of this case study is to show and quantify the effects of mission and aircraft sizing parameters on the mean and variance of direct and total operating cost as well as the required average yield per revenue passenger mile ($/RPM). Finally, the optimal mission requirement settings which yield an OEC that concurrently minimizes the mean $/RPM as well as its variance are identified for the HSCT configuration studied.

† Paper presented at the 18^{th} Annual Conference of the International Society of Parametric Analysts, June 1996, Cannes , France.

Introduction

Over the past few years, research has been conducted by the authors towards developing a comprehensive methodology for the integration of aircraft design with manufacturing and airline business and economics. This initiative has been motivated by a desire to yield an economically viable HSCT. Since an aircraft such as the HSCT has to be economically competitive with respect to current subsonic transports, emphasis has been given throughout this study on understanding and assessing its economic viability. However, economic viability in terms of minimum cost or maximum profit is no longer an adequate and sole concern for a designer. Recognizing the presence of uncertainty in the assumptions made as to fuel price, number of paying passengers, or travel distance, more emphasis has been put on replacing "point" by probabilistic estimates that account and quantify uncertainty of the prediction outcome. In order to implement this objective a methodology called Robust Design Simulation (RDS)[1],[2],[3], that is based on a Concurrent Engineering (CE)/Integrated Product and Process Development (IPPD) approach has been introduced. The procedure for conducting this IPPD approach employs the use of a Design of Experiments (DOE) to facilitate the development of Response Surface Equations (RSE's)[4] which approximate sophisticated, computationally intense disciplinary analyses tools with second (or higher) order polynomial equations. Furthermore, under this new way of thinking the design focus has shifted from optimizing to compromising. Compromising describes a decision process that involves a robust solution[5], i.e. a design that is insensitive to the variation of those parameters that are hard to define. However, such a design might be preferable to a true optimum with low confidence of achieving that optimum consistently.

The purpose of this paper is three-fold. First it introduces and implements a systematic means of achieving robustness in the design solution by extending Taguchi's Robust Design Methodology[6],[7]. Second, it examines and quantifies the effects of mission requirements on the economics of an HSCT. Finally, the paper identifies the mission requirement settings which yield the most robust solution with respect to the average required yield per revenue passenger mile, $/RPM.

Robust Design Simulation

The recently introduced[1],[2],[3] aircraft design methodology called Robust Design Simulation, as depicted in Figure 1, is a multidisciplinary approach to aircraft design. A method which considers concurrently product and process characteristics that are subject to planned or anticipated technology infusions. Product characteristics usually embrace such discipline characteristics as lift and drag for aerodynamics, moments of inertia and structural weight for structures, fuel flow and thrust for propulsion, and so forth. On the other hand, process characteristics capture the effects of producibility, supportability, reliability, and affordability. Under a so called CE/IPPD approach an aircraft synthesis and sizing process, utilizing appropriate analytical tools, evaluates the system value to the customer for each aircraft configuration through selected objectives such as performance, cost, profit, or quality/reliability. Regardless of the defined objective, customer satisfaction is achieved when all system design and environmental constraints are met.

Since any system analysis or optimization is only as good as the contributing analyses, the need for complex discipline-specific analysis capability in the methodology is essential. The need for this capability can be satisfied in two ways: by directly incorporating complex discipline specific codes in the system analysis or by replacing these codes by much simpler equations that capture the essence of these discipline tools. These Response Surface Equations, which are generated through a Response Surface Methodology (RSM)[4], allow one to enhance or improve the synthesis program's analysis capabilities and enable the study of multiple aircraft concepts using higher fidelity analyses. Keeping in mind that in order for the system synthesis to be successful the generated RSEs must be able to accurately represent the data generated by the sophisticated analysis codes.

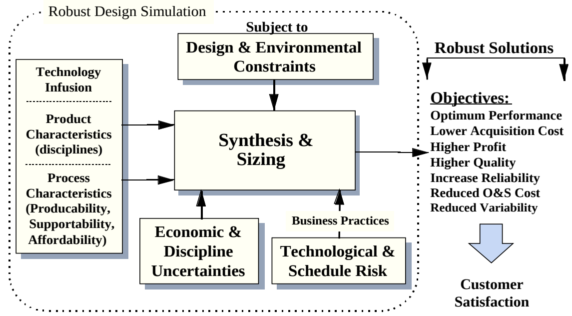

Figure 1: Robust Design Simulation

Furthermore, this new design process is considering the variability of all parameters that are beyond the control of the designer. In particular, one can distinguish between economic and discipline uncertainties, whereas the former includes load factor, cost of fuel, production quantity, while the latter considers variables such as operational air speed or control surface deflections. Technology and schedule risk are two other means that influence producibility and introduce additional uncertainty to the design solution. The uncertainties and risks associated with the system are usually accounted for in form of probability distributions. Therefore, a Robust Design Simulation method is employed that quantifies and minimizes the dependability of the design objective on the design uncertainties and risks. More specifically, optimization procedures focus on finding the optimum settings for a single design point without providing any insight into product performance at off-design conditions[8]. The Robust Design Simulation goes one step further, by accounting for the variability of this optimal solution due to noise factors. The objective is to search the design space for the design variable setting which minimizes the variance and optimizes the mean of the response, hence, yielding a robust design solution. A graphical representation of the concept of moving toward a robust design is shown in Figures 2 and 3.

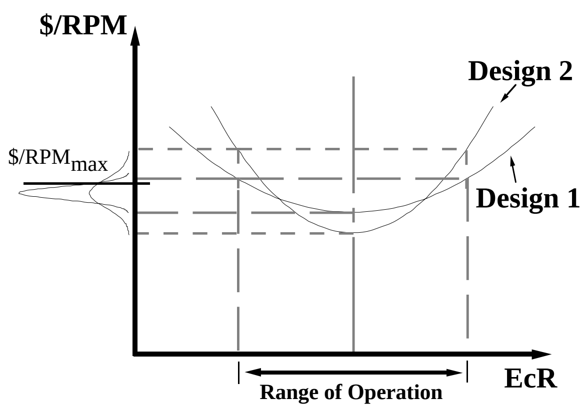

Figure 2: Change in Sensitivity of $/RPM for Two Hypothetical Designs

Figure 2 shows an average required yield ($/RPM) distribution over the range of operation of the aircraft, called economic range (EcR), for two different hypothetical designs. For the same optimal EcR value, the hypothetical Design 2 yields a better point-design-optimal $/RPM. However, since the aircraft will inevitably be operated at off-design conditions, EcR will vary over the assumed operating range. Thus, each design has an associated variation of $/RPM. As can be seen in Figure 2, this variation depends on design variable settings, causing the hypothetical Design 2 to yield a larger variation in $/RPM than Design 1. If the objective is to create a robust design, the hypothetical Design 1 may now become the better design, since even though both distributions for EcR have the same mean, Design 1 yields a higher probability of consistently achieving values for $/RPM close to the desired optimum value. In effect, the better design point performance of the hypothetical Design 2 is traded for the superior off-design performance of hypothetical Design 1.

Essentially, the goal of designing for robustness is achieved by minimizing a configuration's sensitivity to design uncertainty or external factors such as operating condition, environment, etc.[8] This is not accomplished by just optimizing the mean of an objective function, but rather by also minimizing variation, or variance, associated with the selected objective. Taguchi introduced the concept of a signal-to-noise-ratio (S/N) which, if maximized, yields a high signal or benefit with little noise or variation[6],[7],[8]. This solution satisfies the customer requirements while at the same time it is well-balanced in that it performs well under a wide variation of conditions and environments. In an effort to improve on Taguchi's signal-to-noise-ratio concept, a new metric has been introduced for this study, based on more statistical foundations. In this new approach, traditional design objectives such as weight, life cycle cost, or ticket price now become intermediate evaluation metrics used to construct a new objective, the Overall Evaluation Criterion (OEC), which will ultimately be minimized.

This OEC is comprised of the mean and variance of the traditional design objective, which are computed based on the presence of uncertainty variables in the design space. The three equations listed below, are the mathematical formulations of the desired OEC for three different design objectives: minimizing the objective, maximizing it, and optimizing it for a specified target value. Equation (1), the product of variance and the square of the mean, is the analogous to the traditional concept of single objective minimization. Equation (2) is in turn the analogous to single objective maximization. Finally, Equation (3), a weighted average of the variance and the squared deviation from the target, represents the case where the objective calls for a minimization of the deviation from the specified target value. A summation has been employed here rather than a product, since a value for the mean right on the target would yield an OEC of zero regardless of the variance associated with it. In this case, α is an arbitrarily chosen weighing parameter that can emphasize either distance from target value or variation. However, for all three equations, a minimal value for the OEC is desired.

$$\text{OEC} = \text{Variance} * \text{Mean}^2 \quad \text{(minimize mean for traditional objective)} \tag{1}$$

$$\text{OEC} = \text{Variance} / \text{Mean}^2 \quad \text{(maximize mean for traditional objective)} \tag{2}$$

$$\text{OEC} = \alpha * (\text{Mean} - \text{Target})^2 + (1-\alpha) * \text{Variance} \tag{3}$$

Minimizing this set of OECs is equivalent to maximizing the signal-to-noise ratio according to Taguchi's formulation. The two methods differ, however, in the way this OEC or signal-to-noise ratio is obtained. While Taguchi's approach utilizes an inner and outer array for design and noise variables respectively[6],[7], the RDS OEC is based on a traditional DOE implementation which yields a second order equation, RSE, as a function of all key design and noise variables. In this case the noise variables are assigned probability shape functions that yield, through a Monte Carlo simulation, a probability distribution for the objective, $/RPM. This approach to the estimation of the noise factor effects represents a major improvement in accuracy compared to Taguchi's approach.

Methodology Implementation

Since the intent of this study is to provide a measure of achieving a robust design solution for an HSCT, an algorithm has been constructed, depicting all necessary steps. This algorithm is illustrated in Figure 3. This figure depicts implicitly the dependency of the required average yield per Revenue Passenger Mile ($/RPM), Direct Operating Cost (DOC), and Total Operating Cost per trip (TOC) on control terms, such as Payload, design range (Range), percentage of the mission flying in a subsonic regime (%Subsonic), wing area (S), and thrust to weight ratio (T/W), and on economic noise variables, such as Fuel Cost, Utilization, Economic Range, and Load Factor. Load Factor refers in this case to the ratio of the number of passengers boarded on an airplane over the number of available seats. Even though the noise variables are beyond the control of the designer, the dependency of $/RPM, DOC, and TOC on these noise variables can be influenced by the selection of control variables. Thus, while it may be possible to find one setting of design variables (S, T/W,...) which yield a minimum $/RPM, DOC, or TOC over some domain, another series of settings might change the fuel consumption characteristics in such a fashion that the $/RPM, DOC, or TOC *is not as sensitive to* Fuel Cost. This reduces the variability of $/RPM, DOC, and TOC due to noise factors and increases the probability that the design will be economically viable within the pre-specified confidence interval.

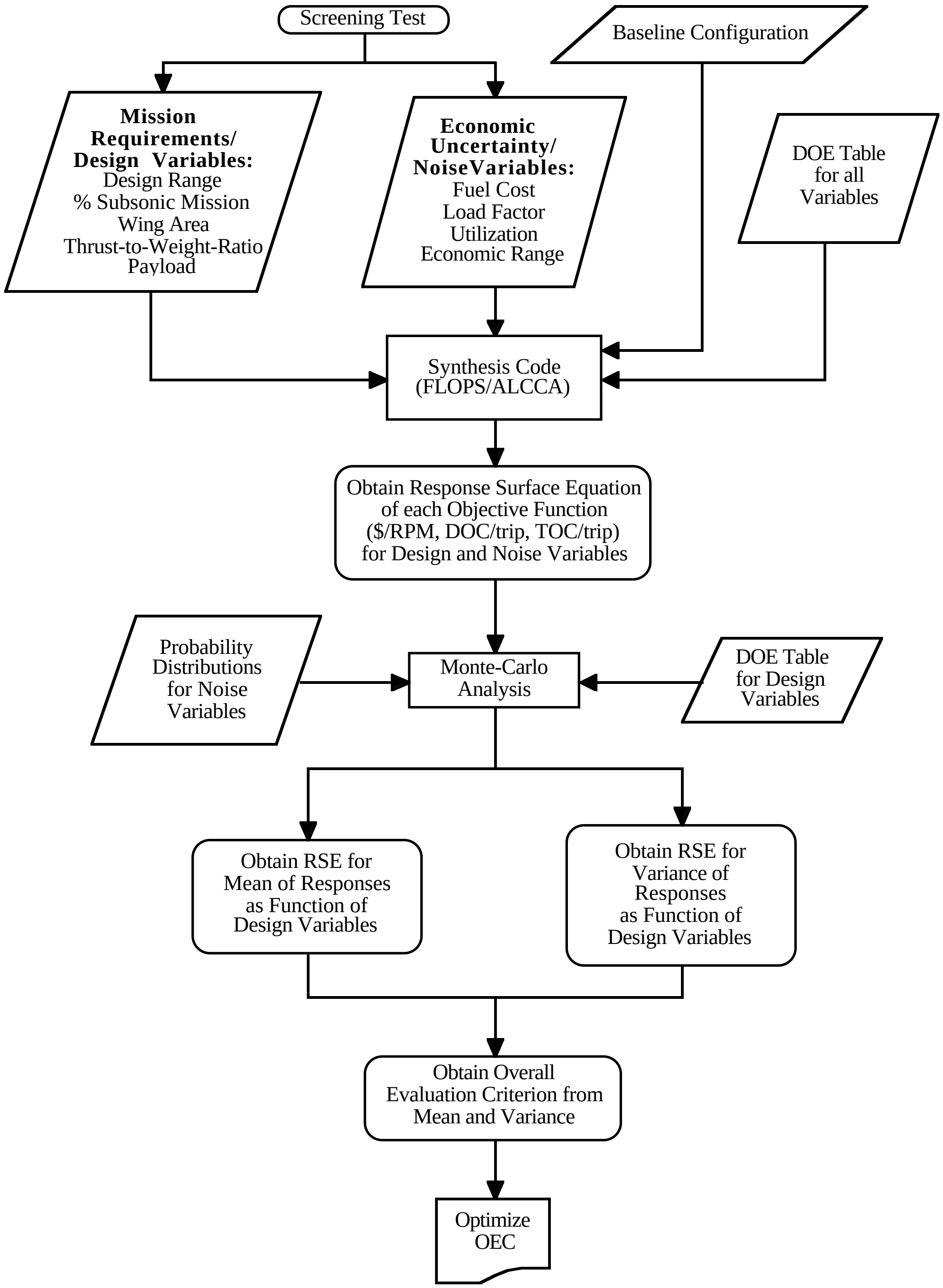

Figure 3: Robust Design Simulation Execution

The baseline configuration used for this study is depicted for review in Figure 4. The baseline aircraft is an area-ruled fuselage (maximum diameter of 12 ft.) with a double delta planform and four nacelles below the wing housing mixed flow turbofan (MFTF) power plants. The values for some of the important baseline design parameters are given below in Table I. The mission definition for this aircraft is seen in Figure 5, where the length of the subsonic cruise of the baseline mission is 15% of the design range. The likely restriction of supersonic flight over land forces the need for modeling a split subsonic / supersonic mission. This subsonic restriction is due to the fact that sonic booms over land are currently not allowed.

Table I: Description of the Baseline HSCT

Parameter	Baseline
Range	5000 nm
Payload	300 Passengers
Fuselage length	280 ft.
Span	77.5 ft.
Sweep 1	74 deg.
Sweep 2	45 deg.
S_{ref}	9,000 ft^2
M	2.4
Cruise Altitude	~63,000 ft.
Sustained Load	2.5 g

For this paper it is assumed that the aerodynamics, structural arrangement, and engine cycle parameters have all been optimized off-line and are set for the purpose of this study. Thus, the aircraft in this case is only allowed to be scaled up or down to accommodate the assigned mission requirement variations.

Figure 4: HSCT Example

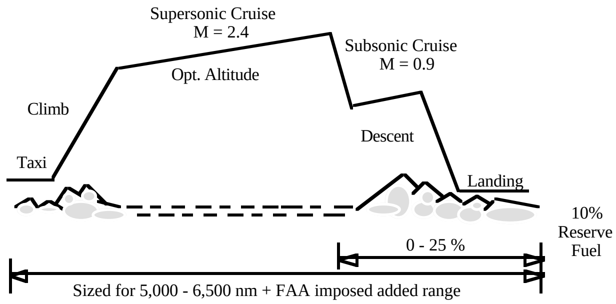

Figure 5: Baseline Mission Profile

According to Figure 3, a synthesis and sizing code must be selected first that allows for perturbation of those input variables of interest. For this study, the Flight Optimization System (FLOPS)[9] code was used for the design simulation, while the Aircraft Life Cycle Cost Analysis (ALCCA)[10] program was selected to be used instead of the economics package within FLOPS to allow for an estimation of such economic output variables as $/RPM, DOC, and TOC. After selecting the synthesis tool, a screening test[11] that monitors the linear sensitivities for all pertinent variables is conducted to identify the most important variables through the use of the Pareto principle[12]. Based on previous studies performed by the authors[1],[2],[3], an inclusive list of design and economic variables were subject to a screening test, which identified the parameters listed in Table II as the main contributors to the responses $/RPM, DOC, and TOC. Thus, the study performed here is based on perturbations of these most influential variables within the design ranges also listed in Table II, while all other, less important variables that are an input into the program are held constant at their most likely or optimal value.

Figure 5 depicts the mission profile for the HSCT that was used for this study. The profile depicts the design range and percentage of the mission that is flown in a subsonic regime. In order to model the economics of the aircraft correctly, a distinction must be made between the Economic and the Design Range. The first represents the average distance a plane will fly from one airport to another during its life, while the latter is the maximum distance a plane is able to fly by design.

Table II: Control and Noise Variable Descriptions and Ranges

		Description	Variable	Design Range
Control Variables	Mission Characteristics	Design Range	*Des-Range* [nm]	5000....6500
		% Subsonic Mission	*%SubsMiss*	0%......25%
	System Sizing	Wing Area	*S-Wing* [sqft]	8500....9500
		Thrust-to-weight-ratio	*T/WRatio*	0.28.....0.32
		Number of Passengers	*PAX*	220.......320
Noise	Economics	Fuel Cost	*$Fuel* [$/gal]	0.55.....1.10
		Load Factor	*LF*	55%.....75%
		Utilization	*U* [hrs/yr]	4500....5500
		Economic Range	*Ec-Range* [nm]	3000....5000

As part of the Response Surface Methodology, a Central Composite Design of Experiment[4] table is set up which defines combinations of the nine variables determined in Table II. The set of these combinations describe the design space while each individual combination represents a separate execution of the synthesis code. An analysis of variance (ANOVA)[11] performed on the DOE response values determines the functional relationship of response ($/RPM, DOC, TOC) and the control and noise variables. For this study, the typically assumed second order regression model[4],[11] is extended with higher order interaction terms to estimate the influence of the design variables on the functional relationship between the responses and the economic variables. Using the obtained RSEs, prediction profiles, depicted in Figure 6, are generated to show the individual dependency or sensitivity of the responses to the nine design and noise variables. All sensitivities are displayed for the baseline aircraft as the variable settings indicate. The noise variables are set in this graph according to their mode values. It must be mentioned at this point that the actual values for $/RPM, DOC, and TOC have been removed to protect any competition sensitive data. Further, it should be noted that the aircraft was sized without applying any external constraints, such as approach speed or landing field length.

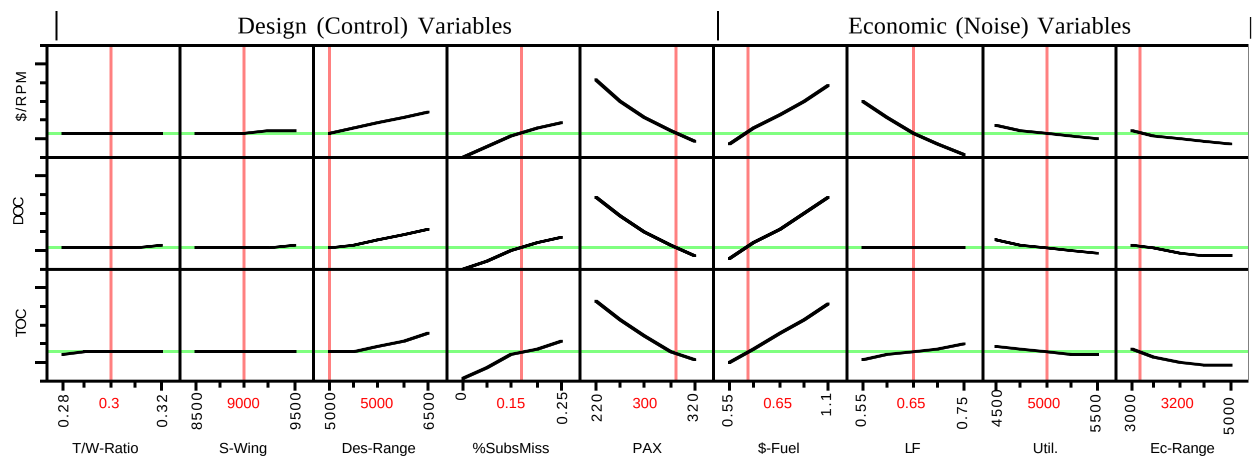

Figure 6: Prediction Profiles for $/RPM, DOC, and TOC

The obtained RSEs for $/RPM, DOC, and TOC can now be employed in a Monte Carlo simulation. The purpose of this simulation is to obtain the mean and variance of the three response distributions caused by the intrinsic distributions of the noise variables. Due to lack of more precise knowledge about these distributions, they are assumed to be triangular. Figure 7 depicts the four distributions marking the range and mode for each variable. In order to identify the dependence of mean and variance on the design variables, another Central Composite Design is set up, this time for the five control variables only. A Monte Carlo Simulation is now executed for each of the cases listed in Table III. Each case sets the control variables to a fixed value while the noise variables are varied according to their distributions as depicted by Figure 7. Hence, each case yields a distribution for $/RPM, DOC, and TOC. By performing multiple Monte Carlo Simulations according to Table III, three sets of means and variances can be obtained for the three responses. A regression analysis for each mean and variance yields six RSEs, which depend only on the control variables. Figure 8 shows a sample distribution from this Monte Carlo Simulation for a case with all design variables set to their mid value. Note that, since the HSCT is a competition sensitive program, all numerical results are presented in form of percent delta with respect to the mean. Thus, the distribution shown in Figure 8 displays the variation of the percent difference in ¢/RPM from the baseline, Δ%¢/RPM, based on 10,000 Monte Carlo Simulation runs.

In a similar fashion, Figure 9 displays the prediction profiles for the six RSEs obtained from the sets of variances and means as a percent difference from the baseline response values. Consequently, the variable settings for the baseline as shown in Figure 9 yield a zero value for the means and a non zero value for the variances. Additionally, Figure 9 depicts the prediction profiles of the Overall Evaluation Criterion (OEC) as defined by Equation (1).

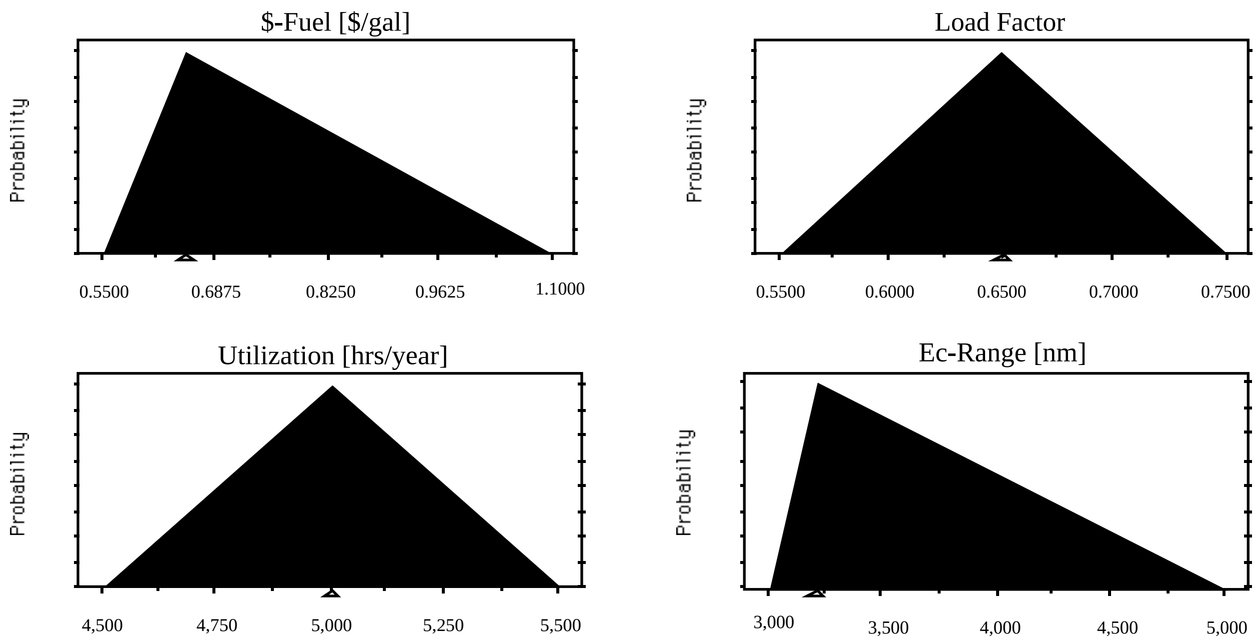

Figure 7: Distribution Assumptions for the Economic Variables

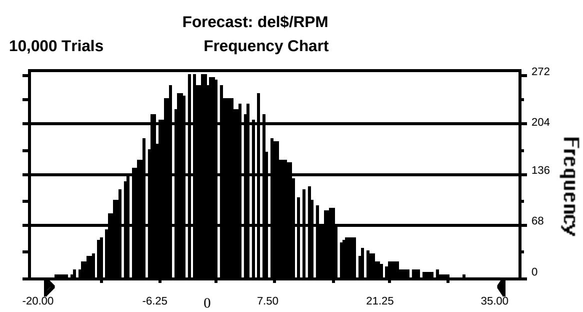

Figure 8: Sample Distribution for Δ%¢/RPM

Table III: DOE Table and Noise Variable Distributions used to Obtain OEC

	Control Variables					Noise Variables				Response		
Exp.#	T/W-Ratio	S-Wing	Des-Range	%Subson Miss.	PAX	$-Fuel	Load Factor	Utilization	Ec-Range	$/RPM	Mean	Variance
1	0.29	8750	5375	0.0625	295						15.79	1.56
2	0.29	8750	5375	0.1875	245						19.96	2.61
3	0.29	8750	6125	0.0625	245						18.67	2.24
4	0.29	8750	6125	0.1875	295						18.32	2.09
5	0.29	9250	5375	0.0625	245						18.19	2.17
6	0.29	9250	5375	0.1875	295						17.55	2.05
7	0.29	9250	6125	0.0625	295						16.44	1.73
8	0.29	9250	6125	0.1875	245						20.92	2.91
9	0.31	8750	5375	0.0625	245						17.94	2.09
10	0.31	8750	5375	0.1875	295						17.52	1.96
11	0.31	8750	6125	0.0625	295						16.44	1.65
12	0.31	8750	6125	0.1875	245						20.90	2.74
13	0.31	9250	5375	0.0625	295						15.99	1.58
14	0.31	9250	5375	0.1875	245						20.19	2.68
15	0.31	9250	6125	0.0625	245						18.86	2.31
16	0.31	9250	6125	0.1875	295						18.62	2.19
17	0.28	9000	5750	0.125	270						18.14	2.18
18	0.32	9000	5750	0.125	270						18.36	2.14
19	0.3	8500	5750	0.125	270						18.07	2.05
20	0.3	9500	5750	0.125	270						18.35	2.21
21	0.3	9000	5000	0.125	270						17.56	1.98
22	0.3	9000	6500	0.125	270						19.16	2.30
23	0.3	9000	5750	0	270						15.91	1.69
24	0.3	9000	5750	0.25	270						19.78	2.67
25	0.3	9000	5750	0.125	220						21.06	2.79
26	0.3	9000	5750	0.125	320						16.31	1.56
27	0.3	9000	5750	0.125	270						18.23	2.15

Discussion of Results

By examining the mean and variance of each response, one can see that the control variables do have an effect on both the mean and variance of the responses $/RPM, DOC, and TOC. However, in the traditional design process, design variables were manipulated only to optimize the mean, neglecting their effect on the variance. The exemplary HSCT study performed in this paper has shown that such an approach can be misleading in aircraft performance or cost prediction. With the consideration of uncontrollable variation in some of the input variables of a system, a new objective has to be identified that can be optimized while accounting for this type of variation.

Usually, a minimization of the response variance is desired in order to yield a high probability of achieving a desired target value[1],[2]. The objective proposed in this study satisfies both needs of optimizing a response value and minimizing its variance. As Figure 9 illustrates, the OEC comprised by Equation (1) is optimized, yielding a robust design solution, by minimizing wing area, design range, and the subsonic mission segment while maximizing number of passengers and seting thrust-to-weight-ratio to the intermediate value. It only so happens that for this study the mean of the average yield per revenue passenger mile ($/RPM), which corresponds to a traditional design objective without considering variation in noise variables, yields the same result for a $/RPM minimization as for the robust design solution. This is due to the fact that both the mean and variance of the responses exhibit the same trend with respect to the control variables in this study.

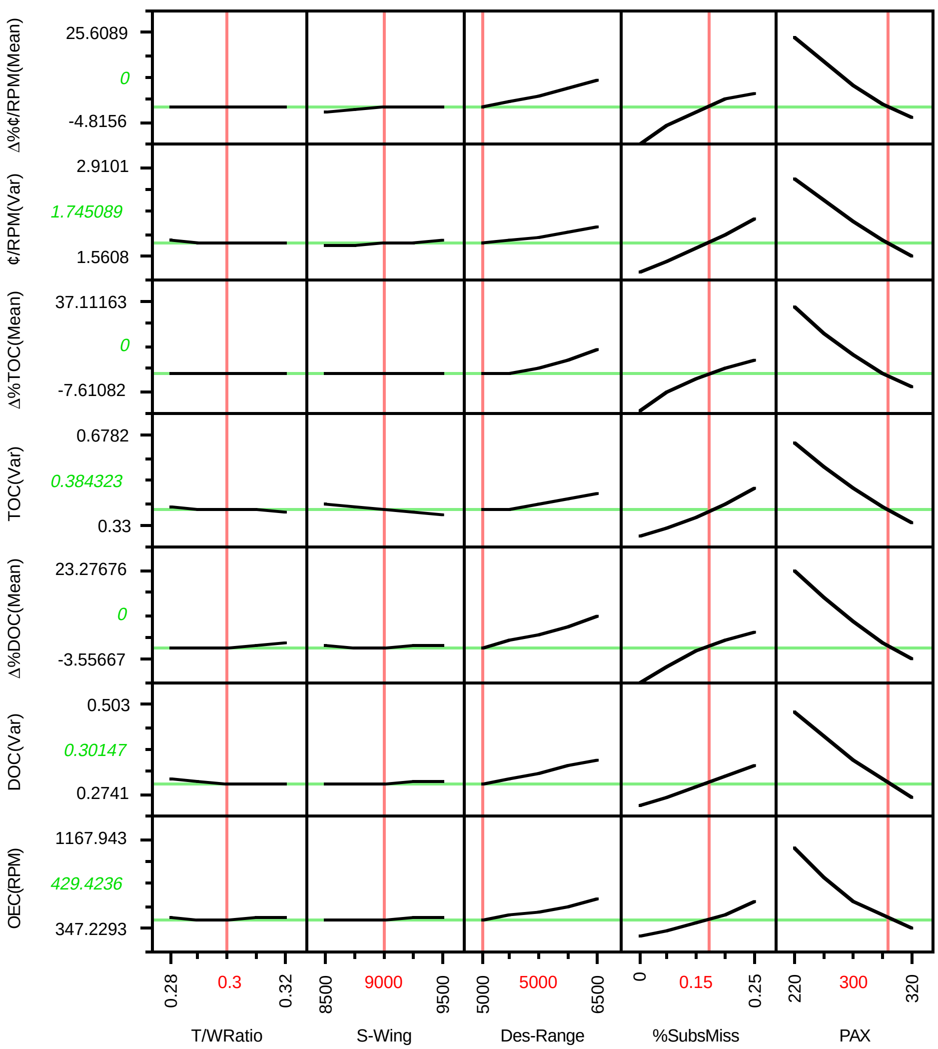

Figure 9: Prediction Profiles for Response Means & Variances and the OEC

Table IV: Robust Design Solution Summary

Parameter	Robust Solution
T/W Ratio	0.3
Wing Area	8500 ft^2
Design Range	5000 nm
%Subsonic Mission	0%
# of Passengers	320

Figure 9 also shows why this does not have to be true in general. For example, examining the TOC response shows that decreasing wing area will leave the mean unaffected but increase its variance a rather undesirable result. Another example is the effect of thrust-to-weight-ratio on DOC. Although decreasing the ratio decreases the mean of DOC, it also increases its variance. Both examples show the need for a design simulation approach that considers both mean and variance concurrently, since a change in design parameters affects both but not in a similar way. The RDS approach as proposed in this paper does account for both while obtaining an optimized, robust design solution. The optimal settings for the problem posed in this paper is summarized in Table IV, depicting the value setting for all design variables.

This robust design solution can be visualized by overlaying the distributions of Δ%¢/RPM for the baseline and the robust design solution as displayed in Figure 10. As can be seen from this figure, the robust design solution improves the mean as well as the variance of the $/RPM distribution yielding a much higher probability of achieving a desired target value.

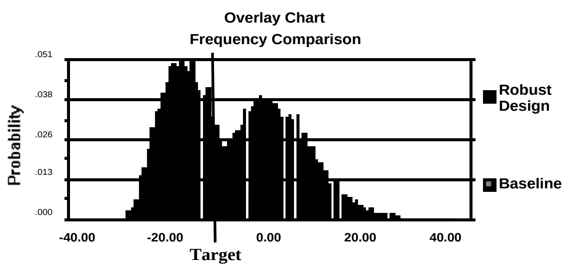

Figure 10: Δ%¢/RPM Distribution for the Baseline and the Robust Design Solution

In order to understand the impact of design range, number of passengers, and percentage of subsonic cruise, the frequency distributions of five different configurations are investigated. The distributions for these five configurations consisting of the robust design solution, an all supersonic baseline configuration, a baseline configuration with maximum (320) passengers, the original baseline, and a baseline configuration with increased range capability (6500 nm) were overlaid and compared against each other, as shown in Figure 11. Again, all distributions are in percent change with respect to the baseline mean. As this figure shows, the robust design solution yields the best result, for a minimum mean and variance of $/RPM. As the sensitivities in Figure 9 indicate, the baseline configuration for an all supersonic flight yields a somewhat better distribution than the maximum passenger configuration. It can also be observed that both yield a better distribution than the original baseline. The configuration with an increased design range has been displayed here also in order to show the effect of increasing the design range in order to reach airports at further distances. Clearly, this would yield an increase in mean and variance of $/RPM compared to the original baseline.

Table V summarizes this result by displaying the mean of the percent change in ¢/RPM with respect to the baseline for each of the five configurations. Additionally, Table V lists the variance of these distributions revealing the same trend as described before.

Table V: Mean and Variance Comparison for Five Different Configurations

Configuration	Δ%¢/RPM (mean)	Δ%¢/RPM (variance)
Robust Solution	-21.13	34.49
all Supersonic	-12.63	47.48
320 Passengers	-2.92	55.43
Baseline	0.0	61.83
6500 nm Des.Range	11.06	74.57

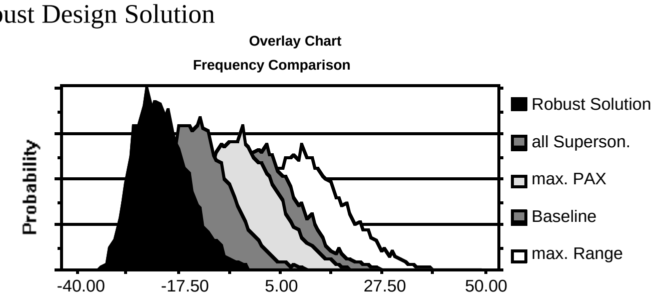

Figure 11: Δ%¢/RPM Distributions Comparison for Different Configurations

Conclusions

This paper provided a step by step approach to defining and implementing design for robustness. Furthermore through the implementation of this approach to an HSCT configuration, the effects of various mission requirements were identified and quantified. The study pointed out quantitatively the adverse effect of the environmental constraint of no supersonic flight over land (thus the requirement for a split sub-/supersonic mission) and the need for an economically robust design. It also illustrated the percent improvement with respect to the presented baseline that could be achieved, if environmental or other mission requirements were to be relaxed in order to yield an optimum solution. Regardless, the approach taken here demonstrates the power of this new method in addressing the economic viability issue in the early design phases where changes can be made without significant cost implications.

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